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Combining Circular and Gauss-Markov Mobility Models (CCGM) for FANET Enhancement

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Abstract

Nowadays, the effectiveness of Flying Ad-hoc Networks (FANETs) has proven their importance in many fields, such as the military, healthcare, entertainment, etc. In such networks, realistic mobility modeling is pivotal for accurately simulating Unmanned Aerial Vehicle (UAV) behaviors and their interactions within the network. To achieve this realism and improve network performance metrics of the network, multiple Mobility Models (MMs) can be integrated, allowing UAVs to exhibit complex movement patterns that reflect real-world dynamics. This paper proposes a combination of Circular Mobility (CM) and Gauss-Markov (GM) models (CCGM) in a superposition mobility model to determine the final pattern of the model and how it affects the Quality of Services (QoS). So, the OMNeT++ was used as a simulation tool to achieve this purpose. The QoS used for analyzing the model are End-to-End Delay (E2ED), throughput, Packet Delivery Ratio (PDR), jitter, and packet loss. The simulation results were introduced and compared with respect to four scenarios. The first two scenarios implied the models independently, while the last two scenarios implied the proposed model (CCGM); each scenario was evaluated with Ad-hoc On Demand Distance Vector (AODV), Destination Sequenced Distance Vector (DSDV), and Greedy Perimeter Stateless Routing (GPSR) routing protocols. The simulation results demonstrate that the proposed model (CCGM) outperforms the GM and CM models in terms of E2ED, PDR, throughput, jitter, and packet loss. Consequently, the CCGM model exhibits an average E2ED of best results with a GPSR of 0.009 seconds in scenario 4, while it exhibits the best results in AODV with PDR of 90.82%, throughput of 669614, jitter of 0.021, and packet loss of 9.18% in scenario 4 as well. This indicates that the CCGM model could enhance the QoS and movement realism, making it useful in FANET applications.

Keywords: Mobility Models, FANET, QoS, Gauss-Markov, Ad-hoc networks, Superposition, Circular model.

1. Introduction

Flying Ad-Hoc Networks (FANETs) are a distinct kind of ad-hoc networks, specifically engineered to facilitate communication among Unmanned Aerial Vehicles (UAVs), known as drones (1). Similar to Mobile Ad-hoc Networks (MANETs), FANETs function without a fixed infrastructure, depending on the dynamic, decentralized interaction of mobile nodes (2,3) (see **Figure 1**). However, FANETs are characterized by their significant mobility and three-dimensional functionality, rendering them ideal for various applications. The emergence and advancement of drones and UAVs have gained significant interest recently since they are utilized in military, surveillance, civilian sectors, health care, disaster monitoring, and environmental research (1,2,4) (see **Figure 2**).

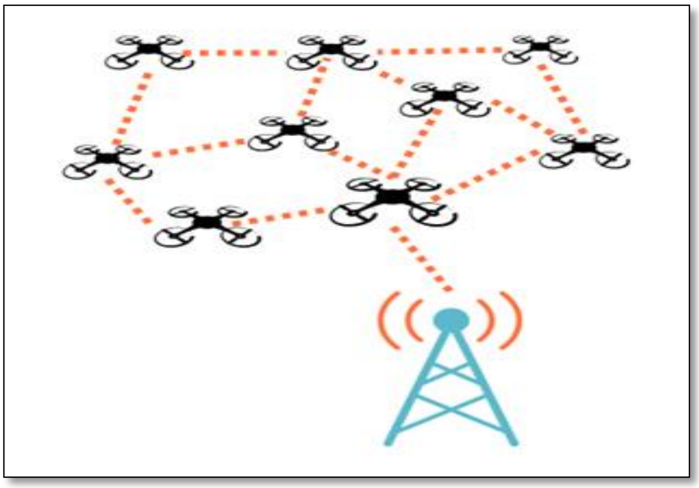


Figure 1. FANET structure

Figure 2. FANET applications

In a highly dynamic environment, FANETs still face challenges in improving Quality of Service (QoS) indicators, such as maintaining connectivity, avoiding packet loss, maximizing packet delivery ratio (PDR) and throughput, and minimizing end-to-end delay (E2ED) and jitter (5). For this reason, mobility models (MMs) in ad-hoc networks are considered one of the proposed solutions in the literature for improving QoS (6), in addition to assessing and improving the performance of routing protocols. Introducing the necessity of modeling realistic mobility patterns is crucial (4, 7–9) as most of the research studies are limited to the conventional MMs, with Random Way Point (RWP) being the most used that simulates unrestricted movement with arbitrary direction and speed variations, offering adaptability but frequently leading to erratic network density (10). The Gauss-Markov (GM) model facilitates smoother and more continuous motion by utilizing previous positions to forecast future trajectories, making it ideal for applications necessitating reliable, predictable connection (1). However, it is primarily appropriate for modelling stochastic motion with inertia despite being insufficient for incorporating deterministic mobility patterns; besides, quality metrics did not reach their optimal values under all environmental situations (4,11). The Circular mobility (CM) model enforces defined trajectories by confining UAVs to circular routes, advantageous for applications requiring continuous coverage of designated areas, such as surveillance or monitoring, but the trajectory is deterministic (2,12). Few researchers (9,13,14) provided the utilization of mixed models, but still limited to the conventional pattern in some manner. This research aims to propose a combination MMs for UAVs in FANET in a creative methodology to:

1. Enhance essential performance measures, including PDR, throughput, E2ED, packet loss rate, and jitter in highly dynamic UAV networks.
2. Establish realistic and stable UAV MMs that accurately represent the intricate dynamics of UAV flight patterns on a large scale.

Unlike previous approaches, the proposed model superimposes motion vectors for the CM and GM MMs. This enables more realistic and adaptable simulation scenarios, including the interaction of structured and stochastic motion in dynamic settings (15).

The rest of this paper is organized as follows: Section 2 provides a summary of the literature review. Section 3 presents the research methodology, including the simulation scenarios and performance analysis. Section 4 conducts the results and discussion. Finally, Section 5 includes the conclusion and future work.

2. Literature Review

Investigating MMs in FANET networks is crucial for assessing the efficacy of diverse network protocols and applications, as well as their discernible influence on QoS (16). Generally, the MMs enhancements are considered a critical issue in UAVs; thus, many studies dealt with it, as in (11) that introduced an enhanced GM model for FANETs. It refined the model to create a 3-dimensional space model that aligns with the movement of UAVs. The model was implemented using NS3, evaluating its performance in terms of PDR, E2ED, and throughput using Ad hoc On-demand Distance Vector (AODV) as the routing protocol, taking into account variations in the number of nodes. The results demonstrated improved link stability and decreased packet loss, making it more appropriate for high mobility and frequent mobility changes, whereas (12) presented a 3D-Semi-Random Circular Mobility model (3DSRCM), which was developed based on the SRCM. The NS3 was used as a simulation tool with a duration of 2000 seconds, a radius in the simulation area of 1000 m, and a 50-150 m range of height. The experiment included two scenarios with 10 and 20 nodes, respectively. The model exhibited enhanced spatial distribution near the search center with enhanced network connectivity. The authors in (17) proposed Anchored Self-Similar 3D GM (ASSGM) to improve PDR, E2ED, and network stability with UAV swarms. They implemented the model in NS3 for 20 UAVs at a speed of 20 m/s for 120 seconds of simulation time and compared it with GM and RWP in AODV and OLSR to demonstrate its superior performance. Other researchers discovered that employing multiple MMs yielded superior outcomes for network quality. Accordingly, the researchers in (9) introduced an integration of the RWP and GM models as a Random Gauss Integrated Model (RGIM) to improve QoS with AODV, Dynamic Source Routing (DSR), and Destination Sequenced Distance Vector (DSDV) to outperform QoS parameters including PDR, throughput, and jitter while lowering delay. The NS2 was utilized as a simulation tool. The integration lets nodes start with random movement by utilizing the RWP and switch to GM-based motion in the chain model for more stable communication with 10 and 50 nodes through 50 and 500 seconds. However, (13) suggested the combined RWP and Manhattan grid models into a chain mobility model to enhance the PDR, throughput, and E2ED in ad-hoc networks. The simulation was executed using NS2 with the DSR protocol, showing good findings across the metrics with a variation of node numbers including 10, 20, 30, and 40 for 300 seconds. On the other side, an identical combination was presented as a hybrid mobility model for the sink mobile node in (14) to enhance data collection. The authors individually compared the proposed model to the RWP and grid MMs, showcasing an increase in data connectivity. The authors suggested that the sink is the only mobile node, operating at a fixed speed of 10 m/s, aggregating data from clusters with variations of 9, 13, 30, and 36. An evaluation of MMs and their impacts on network quality is provided through various studies; such as the authors in (18) who asserted that the GM mobility model and other models significantly impact performance metrics when utilized in the Greedy Perimeter Stateless Routing (GPSR) protocol within FANETs. The GM model provided consistent PDR and sustained moderate E2ED. However, it demonstrated increased routing overhead in comparison to more common MMs, such as RWP. The model ability to maintain smoother paths made it suitable for situations that needed reliable connectivity. The OMNeT++ was used as a simulation tool, with a variation of 20, 50, and 100 nodes. The paper (19) utilized the GM along with the RWP Mobility model to evaluate the performance metrics of the UAV network. The study included 50 nodes with two scenarios varying in node speed (10-50) m/s, while the second included a variation in the packet size (64-1024) bytes. The GM showed the highest PDR and throughput with the lowest latency at the same time with two scenarios compared with RWP; the NS3 was used as a simulation tool.

Table (1) provides a comparison between the proposed model (CCGM) and the existing MMs in the literature. These studies employ traditional models and integrate MMs, but they do not combine CM and GM models, particularly when using the superposition method that combines the models mathematically at each time step.

Table 1. Comparison between the proposed model with previous study models

Ref.	MM	Enhancement	QoS	Findings	Limitations
(11)	Improved GM (IGMMM)	Improve GM by enhancing boundary avoidance, smoother transitions with 3D	PDR, throughput, E2ED	IGMMM outperformed traditional GM in reducing packet loss and improving PDR	The movement pattern still in gaussian pattern; Restricted to the AODV protocol so outcomes may differ with alternative routing protocols; Demands adjustment of alpha and boundary parameters for best outcomes
(12)	3DSRCM (3D Semi-Random Circular Movement) Model	Circular motion with random 3D transitions	Network connectivity, coverage, spatial distribution, smoothness	attains smoother trajectories, expedited coverage, and equitable spatial node distribution.	Initialization requires predetermined pheromone and spiral parameters; increased 3D elevation variations weaken network interaction; The routing protocol is absent.
(9)	RGIM (Random Gauss Integrated Model)	RWP chained with GM	PDR, E2ED, throughput, jitter	Improved QoS parameters for (AODV, DSR, and DSDV) at varying speeds	The traditional movement is still being considered since Each model functions independently; the simulation duration and the number of nodes must be

Ref.	MM	Enhancement	QoS	Findings	Limitations
					proportionately adjusted for both models to be equivalent; the simulation region is restricted to 500 meters only.
(13)	CMM (Chain Mobility Model)	Integration of the Manhattan Grid and Random Waypoint for realistic mobility campus	PDR, throughput, E2ED	Attained enhanced PDR and throughput; suitable for campus and office settings.	Constrained to grid-based topologies, inappropriate for random outdoor environments.
(14)	Hybrid MMs	Adaptive pause durations utilizing Grid and metaheuristic MMs (Tabu Search, Simulated Annealing)	Energy and data collection efficiency	Enhanced data acquisition and energy consumption in clustered wireless sensor networks	Restricted scalability for large-scale installations results from computational overhead.
(17)	ASSGM (Anchored Self-Similar 3D GM)	Implemented spatio-temporal statistical measures for swarm motion.	PDR, E2ED, network stability	Attains enhanced stability and performance in metrics.	Despite using advanced metrics, it uses a single model approach to adapt GM parameters for swarm performance. Did not validate with other performance metrics.
Propos-ed Model (CCGM)	CM and GM combined in superposing method in (AODV, DSDV, GPSR)	CM, GM	PDR, E2ED, Packet loss, throughput, and jitter	Improved all performance indicators with AODV, DSDV, and GPSR; provides a more realistic pattern on a large scale.	Required cubic environment, combing models require computational overhead

3. Research Methodology

Optimization of performance metrics and stable connection with the presence of high mobility is a big challenge. This proposal tackles the optimization of network performance measures in FANETs by integrating two MMs (CM and GM) based on the superposition method. The superposition has been used in mobility modelling to support the classical motion composition of this study. Wherein, distinct movement vectors are combined to replicate intricate behaviors. Unlike previous studies of hybrid MMs that alternated between various movement patterns, this model employs superposition to concurrently integrate multiple patterns. It guarantees a cohesive and accurate depiction of UAVs motion and overcomes the shortcomings of earlier models as mentioned in **Table (1)**. The GM and CM models were specifically chosen to depict stochastic and deterministic patterns respectively. The outputs of these models are mathematically aggregated at each simulation step by vector superposition. The resulting hybrid MMs improve key performance parameters which are PDR, throughput, E2ED, packet loss, and jitter.

The CM model represents a specific case of SRCM (20), whereby randomness is reduced to achieve deterministic motion. In this model, the node remains in a continuous motion with a constant radius and fixed center point, which prevents interleaved transitions among different circular paths. Hence, a constant speed and angle presented the node rotation smoothly without pause times or directional shifts (see **Figure 3**). Furthermore, the nodes positions are calculated during a specific time (21), as in Equation (1):

$$Pc(t) = Cx + r.\cos(wt)\,, Cy + r.\sin(wt), Cz(t) \qquad (1)$$

$$W = v/r \qquad (2)$$

where W is the angular velocity, v is the constant speed, and Cx, Cy, Cz are the center coordinates, and r is the radius.

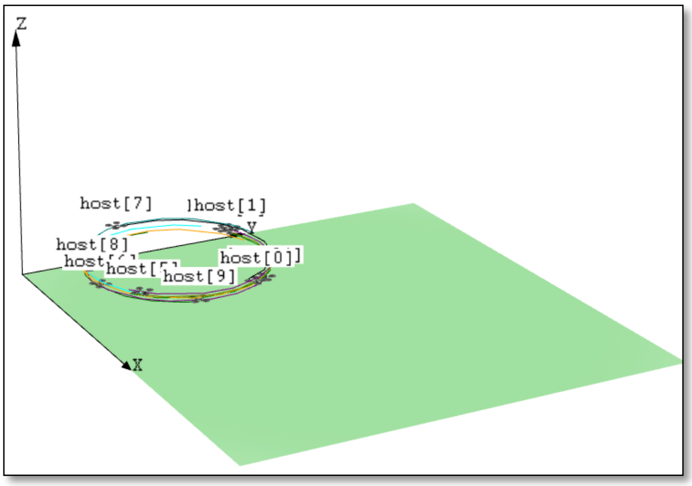


Figure 3. Node trajectory with CM in 3-D.

The GM mobility model was initially introduced for modelling the personal communication system networks (7), which subsequently found widespread application in simulating ad-hoc networks to achieve realistic behavior. This model eliminates the sudden stops and sharp turns found in the Random Walk Mobility Model. This model calculates the updates of the speed, direction, and pitch of a mobile node over time t by considering the values in previous time $t-1$. Consequently, this model exhibits temporal dependency as illustrated in Equations (3-5), respectively (22–24):

$$S_t = \alpha S_{t-1} + (1-\alpha)S^{\sim} + \sqrt{(1-\alpha^2}Sx_{t-1} \qquad (3)$$

$$D_t = \alpha D_{t-1} + (1-\alpha)D^{\sim} + \sqrt{(1-\alpha^2}Dx_{t-1} \qquad (4)$$

$$P_t = \alpha P_{t-1} + (1-\alpha)P^{\sim} + \sqrt{(1-\alpha^2}Px_{t-1} \qquad (5)$$

where, α is the tuning parameter for varying the randomness in the range ($0 \leq \alpha \leq 1$). $S^{\sim}$, $D^{\sim}$, and $P^{\sim}$ representing the average speed, direction, and pitch respectively. Sx_{t-1}, Dx_{t-1}, and Px_{t-1} are random values of the same parameters (speed, direction, and pitch) for the previous time intervals (see **Figure 4**).

The updated positions components (x, y, and z) by considering the angle $\theta(t)$ the XY-plane and vertical angle $\emptyset(t)$ for the Z-axis , as in equations (6-8) (21–23):

$$X(t) = X(t-\Delta t) + S(t).\Delta t.\cos(\theta(t)) \qquad (6)$$

$$Y(t) = Y(t-\Delta t) + S(t).\Delta t.\sin(\theta(t)) \qquad (7)$$

$$Z(t) = Z(t-\Delta t) + S(t).\Delta t.\sin(\emptyset(t)) \qquad (8)$$

By considering the direction vector d as follows :

$$d = \begin{bmatrix} \cos(\theta(t)) \\ \sin(\theta(t)) \\ \sin(\emptyset(t)) \end{bmatrix}$$

The nodes positions updating in GM at time t $PG(t)$ can be expressed by applying the updated speed as in Equation (9):

$$PG(t) = PG(t - \Delta t) + S_t \,.\, \Delta t . d \qquad (9)$$

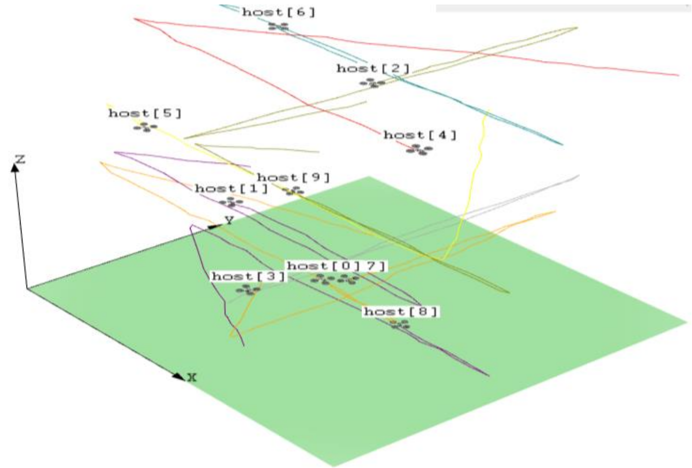


Figure 4. Node trajectory with GM in 3-D

So, by integrating the two models (CM, GM), then the UAVs would demonstrate a combination of predictable circular motion and stochastic variations respectively. Consequently, realistic and adaptable movement patterns would be extracted appropriately for many FANET applications. Additionally, this approach enhances the QoS of communications among nodes, where $PG(t)$ is the extracted position in GM, while Δt represents the pause time (11). The methodological framework is represented by the flow chart in **Figure (5).** which illustrates the initialization, superposition configuration, and execution stages of the proposed model (CCGM). The parameters of each sub-model must be configured (see **Table 2**) (2, 4). Each sub-model creates a vector, PG (Gauss Position) and PC (Circular Position), respectively. The positions are calculated according to the equations (1 and 9). The final position vector is the sum of the position vectors from each sub-model, as shown in Equation (10):

$$P(t) = PG(t) + PC(t) \qquad (10)$$

Table 2. Sub-models parameters

GM parameters	
Parameters	**Values**
Tuning Parameter α	0.5
Mean Velocity	[0,20]
Mean Direction	[0,6.283185307]
Mean Pitch	[0,0.5]
Velocity Stdv.	0.2
Direction Stdv	0.4
Pitch Stdv	0.05
Pause Time	0.1 s
CM parameters	
Center Point (cx,cy)	(1000,1000)
Radius	900 m
Altitude (cz)	uniform(150m, 200m)
Speed	20 m/s

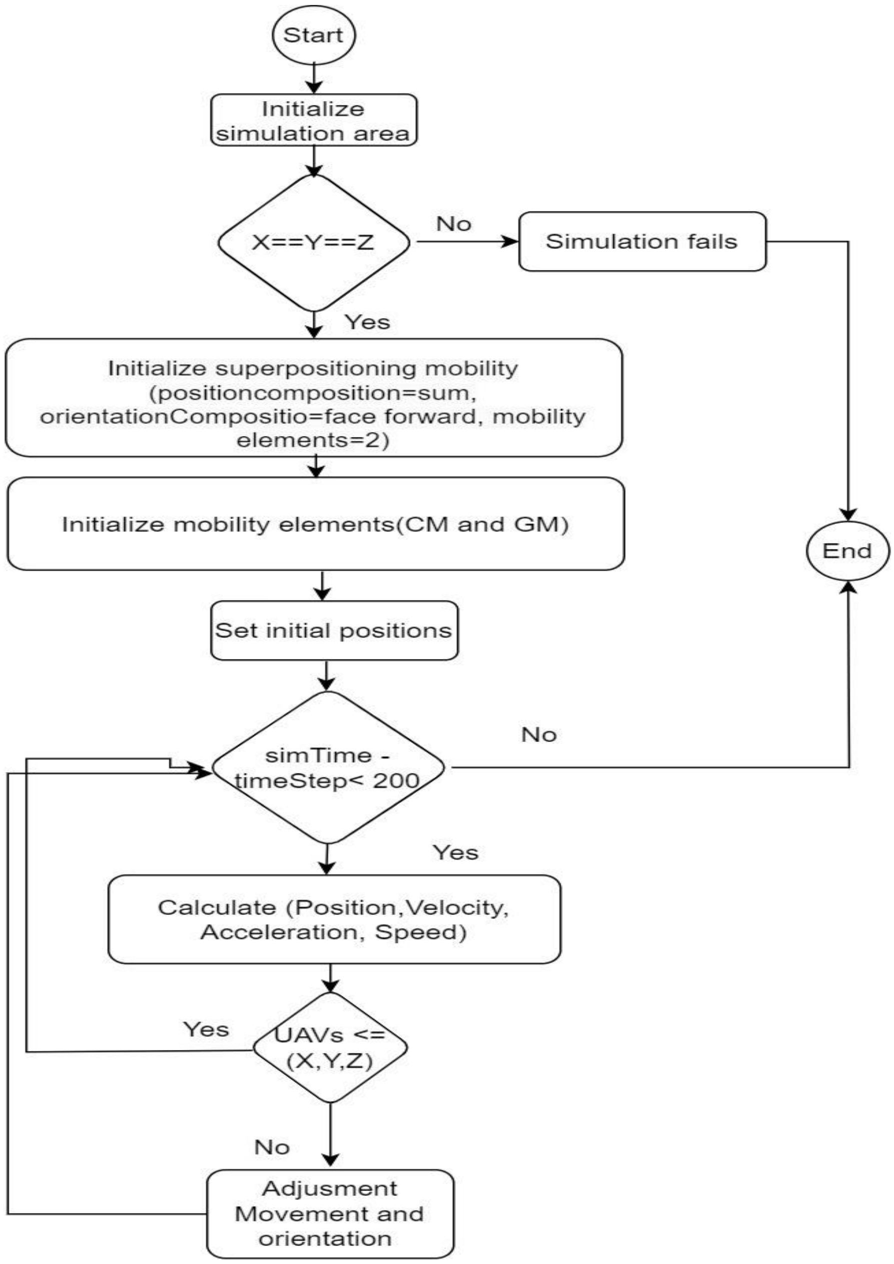


Figure 5. System model flow chart.

The simulation utilizes OMNeT++ as a simulation tool with INET as a framework. **Table (3)** presents the values of the examined parameters for the proposed model.

Table 3. Simulation parameters.

Parameters	Values
Simulator	OMNeT++ 6.0.3/Inet 4.5.3
Routing protocol	DSDV, AODV, GPSR
Mobility models	Circular, Gauss-Markov
Traffic type	UDP
Mac layer protocol	802.11
Number of nodes	10
Node speed	20,10 s/m
Packet size	512 bytes
Data rate	12 Mbps
Simulation area	2000*2000*2000 m
Transmission range	500 m
Simulation time	200 s
Noise application	-90 dBm

3.1. Simulation Scenarios

The experiment was conducted over four scenarios, employing three protocols: AODV, DSDV, and GPSR in each scenario. For Scenario 1, the GM operated independently from the CM; while in Scenario 2, the CM operated independently from GM. In Scenario 3, both combined models (CM, GM) implement the proposed model (CCGM) at uniform velocities of 20 m/s, causing the UAVs to move semi-randomly within a circular boundary (see **Figure 6**). However, in Scenario 4, the proposed model (CCGM) is implemented at various velocities, with CM speed 20 m/s and GM speed 10 m/s, in order to attain superior uniform motion and increased connectivity. The nodes construct an arc trajectory within the movement space without redundancy (see **Figure 7**). **Figure (8)** provides an overview of the CCGM model in 2-D, with **Figure (8 a)** representing the CM, **Figure (8 b)** representing the GM, and **Figure (8 c)** representing the final model after applying the proposed model (CCGM) with Scenario 4.

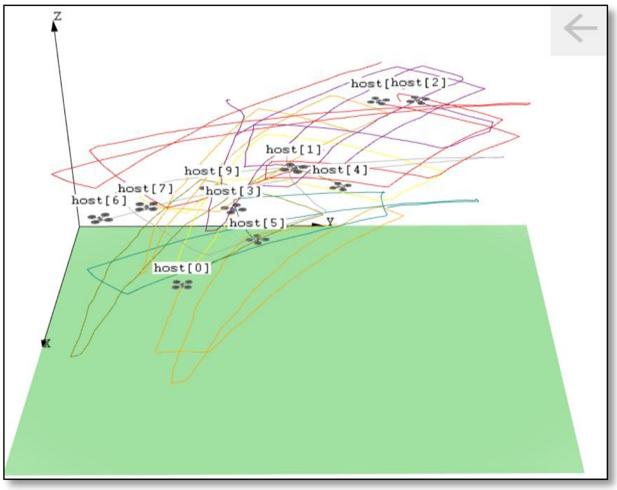


Figure 6. Trajectory of the CCGM with Scenario 3 in 3-D.

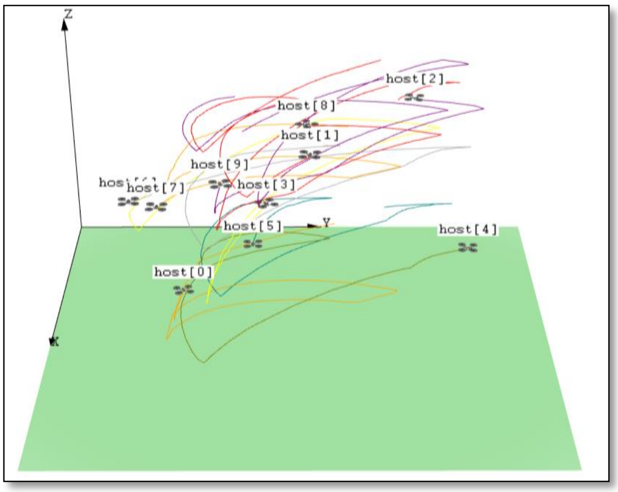
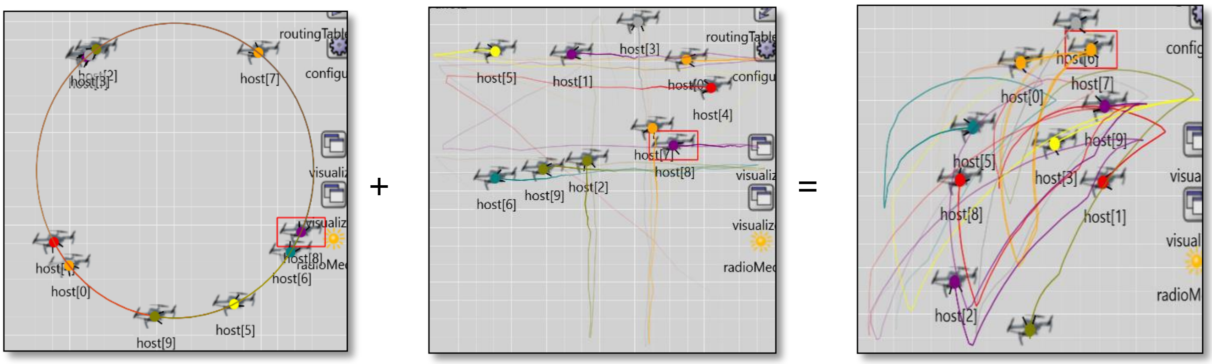


Figure 7. Trajectory of the proposed model with scenario 4 in 3-D



a b c

Figure 8. Implementation of the proposed model (CCGM) in 2-D, where (a) the trajectory in CM, (b) the trajectory in GM, and (c) the resultant trajectory with the proposed model.

3.2 Performance Analysis

One of the most vital aspects of evaluating the proposed model (CCGM) is measuring the QoS through: PDR, throughput, latency, jitter, and packet loss, which are the core metrics that were utilized in the proposed model (25).

3.2.1 Packet Delivery Ratio (PDR)

PDR is an essential metric that indicates the ratio of data packets transmitted by the source to those received at the destination, as shown in Equation (11):

$$\mathrm{PDR} = \frac{\mathrm{R_{pkt}}}{\mathrm{S_{pkt}}} * 100\% \tag{11}$$

where, R_{pkt} is the total number of the received packets by the destination, S_{pkt} is the total number of packets sent by the source. **Figure (9 a)** illustrates fluctuations across the four scenarios. In Scenario 1 (GM), AODV produced a superior PDR greater than DSDV and GPSR. In Scenario 2 (CM), AODV and DSDV produced significant PDR enhancements, although GPSR continues to have difficulties. In Scenario 3, the combined models (CM,GM) are implemented together at the same speed. Generally, all protocols exhibit significant enhancements, mostly with an enhanced PDR in AODV, followed by DSDV. In Scenario 4, CM speed is doubled than that of GM and, thus, AODV achieves the highest PDR and DSDV shows robust performance. However, GPSR demonstrates that the enhancement remains less than other protocols.

3.2.2 Throughput

The throughput is the total number of data packets received by the destination divided by the simulation duration. It is quantified in bits per second, as shown in Equation (12):

$$\mathrm{Throughput} = \frac{\mathrm{R_{pkt}}}{\mathrm{S_{tim}}} \tag{12}$$

where S_{tim} represents the overall duration of the simulation. The throughput analysis indicates considerable discrepancies among the scenarios attributable to the MMs (see **Figure 9 b)**. In Scenario 1, AODV achieves the best throughput and enhances DSDV, whilst GPSR exhibits the lowest efficiency due to high mobility difficulties. In Scenario 2, AODV experiences a substantial fall in throughput, whilst DSDV and GPSR maintain stability, highlighting the influence of deterministic motion on AODV efficacy. In Scenario 3, throughput significantly enhances for AODV and DSDV, with AODV attaining superior performance. In Scenario 4, AODV exhibits robust performance, DSDV maintains its performance, while GPSR demonstrates stable but relatively lower throughput compared to other protocols.

3.2.3 Jitter

Network jitter is the mean of all delay variations for received packets within the same flow. Persistent elevated network jitter can lead to packet loss and network congestion, as in Equation (13):

$$\text{jitter} = \frac{\sum D_{Pn-1} - D_{Pn}}{N_{CP}} \quad (13)$$

where D_{Pn-1} is the amount of the delay to the previous packet, D_{Pn} is the delay amount of the current packet, and N_{CP} is the number of connections. **Figure (9 c)** illustrates the metric values, which reveal fluctuations across the four scenarios. In Scenario 1, GPSR shows the highest result of jitter, but DSDV and AODV have slightly better results. In Scenario 2, GPSR shows higher jitter, although DSDV and AODV show comparable values, reflecting the impact of deterministic motion. In Scenario 3, all protocols demonstrate a substantial decrease in jitter, indicating enhanced stability. In Scenario 4, jitter values are consistently low across all protocols, with slight variations, indicating that the combination technique improves the consistency of packet transmission under regulated conditions.

3.2.4 End-to-End delay (E2ED)

Generally, E2ED denotes the time required to transfer a packet from the source node to the destination node. The average E2ED is determined by dividing the sum of the times taken by all received packets by the total number of packets, as shown in Equation (14):

$$\text{E2ED} = \frac{\sum T_{Pr} - T_{Ps}}{\sum R_{pkt}} \quad (14)$$

where T_{Pr} is the time of the received packet by the destination, and T_{PS} is the time of the sent packet by the source. **Figure (9 d)** reveals that AODV increases E2ED in all scenarios, with Scenario 1 displaying the most insufficient performance. Conversely, DSDV and GPSR consistently attain reduced E2ED, with GPSR exhibiting superior performance overall in Scenarios 3 and 4. This demonstrates that the CCGM model significantly decreases E2ED for DSDV and GPSR, however, AODV continues to encounter elevated delays according to its reactive characteristics.

3.2.5 Packet loss

Packet Loss denotes the occurrence in which data packets sent via a network fail to arrive at their designated destination. It is measured as the percentage of packets failed during transmission to the total number of packets transmitted, as shown in Equation (15):

$$\text{packet loss} = \frac{S_{pkt} - R_{pkt}}{S_{pkt}} * 100\% \quad (15)$$

Figure (9 e), shows significant differences in packet loss caused by the MMs in each scenario. Scenario 1 indicates GPSR suffers highest packet loss, succeeded by DSDV and AODV, attributable to the stochastic nature of node movement. In Scenario 2, GPSR continues to exhibit significant packet loss, whereas DSDV and AODV demonstrate enhanced performance due to deterministic mobility.

In Scenario 3, packet loss significantly decreases across all protocols, with AODV that shows the least loss, signifying enhanced stability and coordination. In Scenario 4, GPSR demonstrates consistent packet loss, whereas DSDV and AODV sustain low levels, highlighting the beneficial effects of the combined approach with increased circular speed.

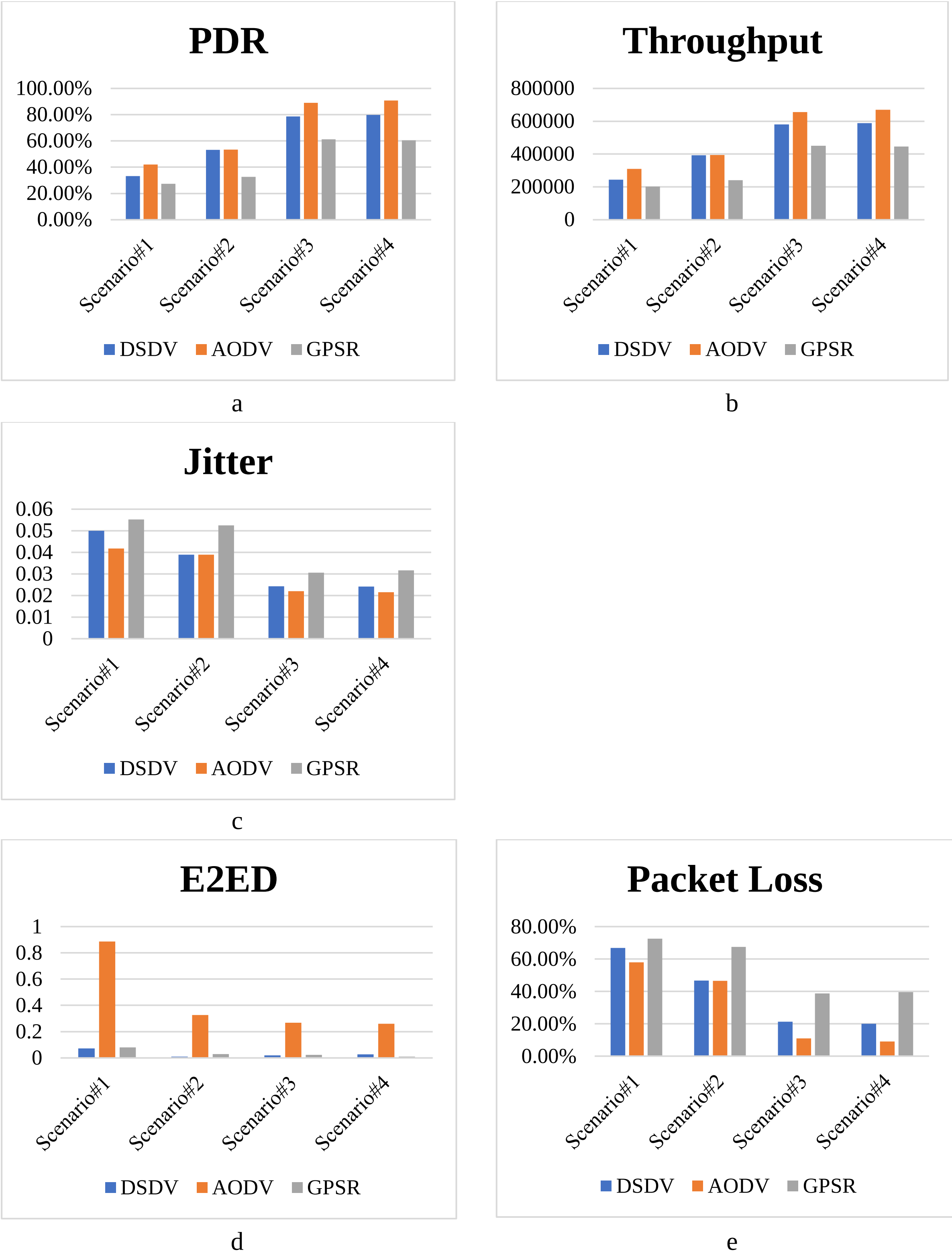


Figure 9. Performance metrics analysis for GM in comparison to the CCGM model, where (a) PDR, (b) Throughput, (c) Jitter, (d) E2ED, and (e) Packet loss.

4. Results and Discussion

This section discusses the examined parameters, **Table (4)** displays the simulation results for the PDR, throughput, jitter, E2ED, and packet loss with the four scenarios: Scenario 1 implied GM, Scenario 2 implied CM, Scenario 3 implied the proposed model as CM and GM with 20 m/s, while Scenario 4 implied the proposed model for CM with 20 m/s and GM with 10 m/s. The PDR achieved the best result in Scenario 4 with 90.82% in AODV, outperforming GM by 48.77% and CM by 37.32%. The DSDV achieved its best result with

Scenario 4 as well, recording 79.90%, while the GPSR achieved its best result with Scenario 3, recording 61.15%.

Similarly, in terms of throughput, the AODV achieved the best result of 669614 in Scenario 4, which improves the GM and CM by 359547 and 275169 than GM and CM, respectively. The DSDV achieved its best result in Scenario 4 by 589087, whereas the GPSR achieved 445768 in Scenario 4 as the best result. In terms of jitter, the AODV achieved the best result in Scenario 4 with 0.02159, outperforming the GM and CM by 0.02028 and 0.01742, respectively. The DSDV also achieved the best results by 0.02424 in Scenario 4, while the GPSR achieved its best result by 0.03057 in Scenario 3. In terms of E2ED, the GPSR outperformed GM at 0.06973 and CM at 0.01811 in Scenario 4 by achieving 0.00988 as the best result. The DSDV yielded its best result with Scenario 3 at 0.019363, whereas AODV results revealed a higher value in Scenario 4 with 0.25896.

As for the packet loss, the AODV recorded 9.18% in Scenario 4, indicating that the proposed model outperformed GM by 48.77% and CM by 37.32%. The DSDV yielded 20.10% as the best result in Scenario 4 as well, whereas GPSR recorded its best result in Scenario 3 by 38.85%.

Table. 4 Simulation results

Routing protocol	Metric	Scenario #1	Scenario #2	Scenario #3	Scenario #4
AODV	PDR	42.06%	53.50%	89%	90.82%
	Throughput	310067	394445	656179	669614
	Jitter	0.04187	0.03901	0.02206	0.02159
	E2ED	0.88596	0.32545	0.268	0.25896
	Packet loss	57.94%	46.50%	11%	9.18%
DSDV	PDR	33.15%	53.22%	78.74%	79.90%
	Throughput	244408	392397	580567	589087
	Jitter	0.05003	0.039	0.02427	0.02424
	E2ED	0.07267	0.00914	0.019363	0.02708
	Packet loss	66.85%	46.78%	21.26%	20.10%
GPSR	PDR	27.43%	32.56%	61.15%	60.46%
	Throughput	202260	240026	450847	445768
	Jitter	0.05526	0.05256	0.03057	0.03164
	E2ED	0.07961	0.02799	0.02301	0.00988
	Packet loss	72.57%	67.44%	38.85%	39.54%

5. Conclusion and Future Work

This paper proposes combining Circular Mobility (CM) and Gauss-Markov (GM) models in superposition mobility model (CCGM) to improve FANET performance metrics. The proposed model significantly improves the performance of FANETs by enhancing throughput and PDR, diminishing E2ED and jitter, and minimizing packet loss. The simulation was conducted in OMNeT++/INET with four scenarios; each scenario was evaluated with AODV, DSDV, and GPSR. Scenarios 1-2 included GM and CM respectively as independent models, while scenarios 3-4 included the CM combined with the GM mobility model (CCGM) as a proposed model. In Scenario 3, the speeds of the sub-models within the proposed model were identical, whereas in Scenario 4, the speed of the CM is double than that of the GM, making it more organized and realistic. The results were obtained in scenario 4, the average E2ED scheduled the best result with GPSR at 0.009 seconds, while the AODV showed the best results with PDR at 90.82%, throughput of 669,614, jitter of 0.02159, and packet loss of 9.18%. This indicates that the CCGM can enhance the performance metrics, showing the model's adaptability and efficacy in optimizing network performance. These improvements are essential for facilitating real-time and mission-critical UAV applications, guaranteeing efficient and reliable network connections in highly dynamic aerial environments, especially with large scales like 2000 meters. The CM and GM combination (CCGM) in the superposition approach effectively addresses the challenging mobility constraints in FANETs. Therefore, it is recommended to utilize the superposition approach with other traditional MMs for further enhancements and to facilitate more robust and high-performing UAV-based communication networks. Finally, as future perspectives, evaluating the CCGM model could be performed against other conventional models, extending the simulation scenarios to encompass more UAVs in the FANET, and utilizing other protocols.

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Conflict of Interest

The authors declare that they have no conflicts of interest.

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